Refine Search

Search Results -

Terms	Documents
L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	1

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search:

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, September 26, 2007 Purge Queries Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB; PLUR=YES; OP=OR		
L39	L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	1	L39
	DB=EPAB,JPAB,DWPI,TDBD; PLUR=YES; OP=OR		
L38	L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	0	L38
	DB=DWPI,TDBD; PLUR=YES; OP=OR		
L37	L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	0	L37
	DB=EPAB,JPAB; PLUR=YES; OP=OR		
L36	L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	0	L36
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L33	("20030093347")[URPN]	0	L33
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L30	("20070156574")[PN]	1	L30
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L27	707/1	10126	L27
L26	709/226	6335	L26
L25	L24 and offset	8	L25
L24	L22 and delta and gamma and threshold and calculation	19	L24
L23	L22 and (delta with utilization with threshold or delta near utilization near threshold or delta adj utilization adj threshold)	1	L23
L22	L21 and (trad$ near engine or trading with engine or trading adj engine or trading near software or trading with software or trading adj software)	1598	L22
L21	(internet or www or network)	1588126	L21
L20	709.clas.	57760	L20
L19	705.clas.	53838	L19
L18	705/1	7650	L18
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L16	'6360210'.pn.	1	L16
L15	'6263321'.pn.	1	L15
L14	'6263321'.pn.	1	L14
L13	'6282521'.pn.	1	L13
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=YES; OP=OR		
L12	L11 and gamma and delta and vega	10	L12
L11	L10 and (order with risk or order near risk or order adj risk)	84	L11
L10	l9 and (hedge or hedg$)	130	L10
L9	L8 and (variable or vary or varing)	168	L9
L8	L7 and option near3 pric$	198	L8
L7	L6 and (trad$ or buy$ and sell$)	25574	L7
L6	(derivative near product or derivative with product or derivative adj product)	121523	L6
L5	705/38	1305	L5
L4	705/37	3199	L4

L3	705/36	1780	L3
L2	705/36r	263	L2
L1	705/35	3258	L1

END OF SEARCH HISTORY

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BAMP

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Few Options

(Treasurers can use either very expensive software or simple spreadsheets for tracking derivatives trading; article offers buyer's guide)

Article Author: Moules, Jonathan
Treasury & Risk Management , v 9 , n 6 , p 39-42
August 1999
Document Type: Journal **ISSN:** 1067-0432 (United States)
Language: English **Record Type:** Fulltext; Abstract
Word Count: 2216

Abstract:
Derivatives are used more and more as a risk management tool but the cost of derivatives tracking software has prohibited most treasurers from investing in derivatives tracking software. Using this type of software also entails changes in derivatives dealing processes. For some companies, investing in these solutions is not urgent for the need to integrate front-office and back-office systems and the entire corporate infrastructure is given a higher priority. Companies that can not afford to invest in software programs make do with spreadsheet packages. Accomplishing tasks by using spreadsheets may be time-consuming but results in more diligent work since an understanding of the dynamics of the task are required. On the other hand, spreadsheets pose risks to security due to lack of built-in levels of authority to control access to data. Article includes a buyer's guide on derivative software packages.

Text:

Treasurers wanting to track derivatives trading have two choices: very expensive software packages or good old-fashioned spreadsheets.

BY JONATHAN MOULES

Last January, Scott Lynch decided it was time to stop procrastinating and finally confront the year 2000 issue. To guard against any disruption, Lynch, the financial systems manager at Gtech, the $1 billion computer outfit in West Greenwich, R.I. that specializes in lottery systems, decided to upgrade its enterprise resource planning (ERP) software.

Gtech's supplier SAP, the German software giant, was happy to oblige. As a bonus, it also installed its SAP Treasury system as well, a pricey tool for tracking derivatives trading. Previously, this software had only been available to buy. "It is not cheap to upgrade a system," says Lynch, who won't say how much he spent. "But we knew that we were getting a good deal with the SAP Treasury software thrown in." He uses it to manage the company's foreign exchange exposures in Australia, Belgium, Canada, Poland and Singapore.

Treasurers increasingly use derivatives as a risk management tool. However,

because the cost of derivatives tracking software remains steep--packages cost in the six figures--most treasurers do the job with little more technological support than an Excel spreadsheet.

Money is not the only deterrent. Treasurers might have to change their derivatives dealing processes if part of that process is computerized, explains Roger Shannon, assistant treasurer at $1.9 billion Brown-Forman, the wine and spirits exporter based in Louisville, Ky. "Treasury departments have very different procedures for the same tasks," Shannon notes.

The SAP Treasury package covers more than just derivatives trading. It also has a cash management function. By linking SAP's software to another program, Cerg Finance, supplied by XRT Cerg Finance, Gtech's treasury team has fully automated its communication with the firm's banks. Rather than calling each bank to deposit customer payments, the team can now sit back while the SAP-Cerg combined system automatically puts the money into the correct bank accounts through an e-mail.

At Brown-Forman, the nine-person treasury team does not have the luxury of using SAP's derivatives software. But they have created an archive of share price information to analyze derivatives performance by linking SAP's ERP software to the online news feed of Reuters. The key to the link is Fxpress, the eponymous derivatives software product of the computer company based in Bala Cynwyd, Pa. FXpress pulls the latest share prices from Reuters and stores the data for up to six months in a data base. The market information captured is also used to produce performance measures for each of Brown-Forman's derivatives and forwards contracts.

Now, when assistant treasurer Shannon and his team make their periodic visits to the banks, they have the best possible bargaining position because they hold the information on exactly how well their derivatives contracts have fared. "Before FXpress," Shannon says, "we could spend a day and a half marking to market. That is time that could be better spent analyzing our exposures."

Few treasury departments have made as much use of integrated technology as Gtech and Brown-Forman, according to David Furlonger, research director at $642 million Gartner Group, an independent provider of information technology research and analysis, based in Stamford, Conn. "Many corporate treasury departments still rely on disparate technology to service their business," Furlonger notes.

Integration Remains Poor

Moreover, the adoption of clever computer systems to manage derivatives dealing is still a distant goal for many companies. "Although Reuters terminals are common," Furlonger says, "integration of front-office and back-office systems remains poor, as does integration to the entire corporate infrastructure. Spreadsheets are pervasive."

Microsoft's Excel spreadsheet package is quite adequate for the likes of Volt Information Services, a $1.7 billion New York-based company that provides temporary recruitment and computer consultancy. The low cost of

using Excel is one of its big selling points, explains Treasurer Ludwig Guarino. He says that if derivatives software suppliers are to broaden their market share, they must develop more affordable systems. "The software companies don't seem to make any products for the low end of derivatives dealing," Guarino argues. "The products that exist tend to be high-end software providing much more (functions) than we need."

A spreadsheet is not ideal, Guarino admits, but sometimes less technology produces more diligent work. "A spreadsheet encourages people to understand the dynamics behind what they are doing," Guarino says. "When using a packaged software system, people are just inputting numbers and not necessarily understanding the mechanisms behind the calculation."

But spreadsheets pose risks to security, says John Schoonbrood, treasurer at $223 million J.D. Edwards, a Denver-based company that develops ERP software but also buys derivatives systems to manage its own financial risk. "When you deal with foreign currencies, you want to have absolute security that the information you have is right," Schoonbrood explains. "Spreadsheets are a more risky approach because they have no in-built levels of authority to control access to the data.

With derivatives contracts in the high millions, J.D. Edward's treasury team cannot afford to rely on spreadsheet technology alone. Schoonbrood's group still makes trades over the telephone, supported by information from a wire service. However, details of the transaction need only be keyed into the system to provide a permanent records for future reference and historical comparisons.

Price is also a concern. "If we weren't such a global operation. Schoonbrood says, referring to the fact the J.D. Edwards operates in more than 100 countries, "I don't think the cost of a treasury management system would be justified."

Of course, a computer package is only as good as the people using it, says Jeff Wallace, managing partner at Greenwich Treasury Advisors, a treasury consultancy based in Greenwich, Conn. "There is a risk that you buy a computer package and do not know what goes into the system's market model," he explains. "Every so often, you should test your market models, because markets change along with bank pricing models."

Derivatives Software

Company	Product
Algorithmics 185 Spadina Ave. Toronto, Ontario M5T 2C6, Canada Tel: (416) 217-1500 Fax: (416) 971-6100 www.algorithmics.com	Algo Suite
Derivatives Consulting 2333 Kapiolani Blvd., #3310 Honolulu, HI 96826 Tel: (808) 955-2283 Fax: (808) 947-6588	Trade Smart

www.dercon.com	
FinancialCAD 7565 132nd St., Suite 207 Surrey, British Columbia V3W 1K5, Canada Tel: (800) 304-0702 Fax: (604) 572-3684 www.financialcad.com	FinancialCAD for Excel
Financial Software Systems 250 W. 57th St., Suite 1420 New York, NY 10019 Tel: (212) 265-6864 Fax: (212) 265-6908 www.fssnet.com	Spectrum
FXpress 111 Presidential Blvd., Suite 227 Bala Cynwyd, PA 19004 Tel: (610) 717-7988 Fax: (610) 717-7983 www.fxpress.com	FXpress
GE Information Services 401 N. Washington St. Rockville, MD 20850 Tel: (301) 340-4665 Fax: (301) 340-5250 www.geis.com	Risk Exposure Management System (RXM)/Trinity
Infinity 560 Lexington Ave. New York, NY 10022 Tel: (800) 827-2323 Fax: (212) 371-1148 www.infinity.com	Infinity 7, Panorama, Infinity Forex, Opus, The Devon System
Inssinc 300 Broadacres Dr. Bloomfield, NJ 07003 Tel: (973) 338-0321 Fax: (973) 338-0397 www.inssinc.com	Futrak NT
IQ Financial Systems 130 Liberty St. New York, NY 10006 Tel: (877) 240-4737 Fax: (212) 250-3253 www.iqfinancial.com	Trade IQ
KPMG Information Solutions Metro Center One Station Pl. Stamford, CT 06902 Tel: (203) 353-4850 Fax: (203) 353-4870 www.kpmgis.com/product/	Quantum Treasury Management Solution
Monis Software 122 E. 42nd St., Suite 2815 New York, NY 10168	Monix XL

Tel: (212) 573-6733 Fax: (212) 573-6740 www.monis.com	
SAP America 3999 W. Chester Pike Newtown Square, PA 19073 Tel: (610) 355-2500 Fax: (610) 335-2501 www.sap.com	SAP Corporate Finance Management
--	SAP Treasury
Savid International P.O. Box 238 Suffern, NY 10901 Tel: (914) 362-1252 Fax: (914) 362-4524 www.savid.com	Savid System
Selkirk Financial Technologies 475 W. Georgia St., Suite 430 Vancouver, British Columbia VSB 4M9, Canada Tel: (604) 682-2862 Fax: (604) 682-1059 www.selkirkfinancial.com	Treasury Manager
Summit Systems 22 Cortlandt St. New York, NY 10007 Tel: (212) 896-3400 Fax: (212) 896-3434 www.summithq.com	Summit Systems
Theoretics P.O. Box 725 Park City, UT 84060 Tel: (800) 255-0035 Fax: (435) 655-3359 www.theoretics.com	Telemark

Company	Price
Algorithmics	Starts at $270,000
Derivatives Consulting	$199
FinancialCAD	From $795
Financial Software Systems	$300,000 and up
FXpress	Annual license fee from $39,000
GE Information Services	Varies
Infinity	Varies according to platform and number of users.
Inssinc	License fee from $100,000
IQ Financial Systems	Varies
KPMG Information Solutions	$250,000 and up, depending on number of users, sites and modules
Monis Software	$5,000 - $25,000
SAP America	Varies
--	Free to users of SAP R/3

	version 4.5
Savid International	$60,000 - $250,000
Selkirk Financial Technologies	$50,000 - $150,000
Summit Systems	Varies
Theoretics	$80,000 for two workstations
Company	Description
Algorithmics	A family of integrated software components to support all elements of risk management.
Derivatives Consulting	Software for calculating prices and managing a comprehensive range of derivatives products. The system includes caps/floors, a futures strip model and a forward volatility matrix.
FinancialCAD	Financial instrument modeling software for spreadsheets. Supports bonds and bond derivatives, commodity, equity and foreign-exchange derivatives, as well as structured-interest-rate products.
Financial Software Systems	A family of software packages, integrating front-middle and back-office functions for foreign-exchange and interest-rate instruments.
FXpress	Integrated foreign-exchange software that can capture details of spot, forward and option trades, maintain counterparty limits and produce bank performance statistics.
GE Information Services	A risk-and-exposure management system that tracks credit risk in real time. It can be linked to the Trinity trading and risk management software to provide global credit and market risk.
Infinity	An integrated suite of applications covering a range of risk-management tasks, from transaction processing to decision

	report. Functions include a limit manager, which helps control allocation and usage.
Inssinc	Real-time online derivatives processing software for treasury departments and capital markets. Covers deal capture, risk management, settlements and multi-currency accounting.
IQ Financial Systems	A complete trading system for capital markets. Consolidates trade and cash-flow data to provide reporting across multiple products.
KPMG Information Solutions	Powerful treasury management software, encompassing treasury, accounting and cash management functions as well as full pricing models for all commonly traded financial instruments.
Monis Software	A family of software products, providing derivatives analysis and management across most classes of vanilla and exotic instruments.
SAP America	Comprehensive system, combining a derivatives package with SAP's business information software, R/3.
--	Specialist software for treasury transactions, covering cash management, market risk management and treasury management functions.
Savid International	Financial application software package that processes and analyzes all activities related to debt and derivative portfolios.
Selkirk Financial Technologies	Treasury integration system that manages trading and hedging activities, including foreign-exchange and commodities-risk

	management.
Summit Systems	Derivatives trading and global risk management system. Includes pricing, hedging and analytics, value-at-risk methodologies, risk/credit management, accounting.
Theoretics	Derivatives portfolio analysis system for a range of transactions involving interest rates, currency, equity and commodities. Can calculate value-at-risk data base information.
Company	Specialty
Algorithmics	Calibrates pricing models to market prices for scenario analysis, value-at-risk calculation and Monte Carlo simulations
Derivatives Consulting	All models are written in Excel, so the code is visible. Prices and manages 31 types of standard and exotic options and eight kinds of swaps.
FinancialCAD	Supports value-at-risk using the delta-normal or lienar value-at-risk method, based on the methodology specified by J.P. Morgan's RiskMetrics.
Financial Software Systems	Users of the full system can see positions updated in real-time. Spectrum can be bought as a complete system or as separate packages.
FXpress	A comprehensive system, including real-time data feeds from the largest business news organizations and strong counter-party risk capability.
GE Information Services	Enables users to react quickly to market changes and is flexible enough to adapt to different styles of exposure management.
Infinity	Comprehensive coverage of trading, processing and risk management. A global

	network of sales and support teams.
Inssinc	Advanced audit features to track changes in a database to control front-, middle- and back-office processing.
IQ Financial Systems	Capacity to handle high transaction volumes and real-time performance. A flexible design to meet changing commercial and regulatory requirements.
KPMG Information Solutions	Ideal for larger
companies	that need the latest technology. Installed by specialists in treasury and finance operations.
Monis Software	Available as an Excel add-in, a suite of ActiveX components and a collection of dynamic link libraries.
SAP America	Ensures that general ledger, strategic enterprise management and other data flows around the company are helping.
--	Complete software package for efficient management of liquidity, portfolios and risk.
Savid International	Comprehensive list of functions, including mark-to-market, portfolio analytics, risk management, interest accrual and payment processing.
Selkirk Financial Technologies	The system's 10 components are fully integrated, so relevant data is completely accessible. It can also prepare more than 60 types of reports for forecasting, trading and hedging.
Summit Systems	Advanced technology system for fast, reliable implementation of trades.
Theoretics	Includes an interest rate-curve builder, and the user can perform dealer-quality risk analysis across the entire portfolio.

Company	Drawbacks
Algorithmics	Not a straight-through processing system with front-office trading functions.
Derivatives Consulting	Addional software needed for more advanced derivatives management functions, such as real-time market tracking.
FinancialCAD	A very basic derivatives software package.
Financial Software Systems	The software is expensive.
FXpress	Limited to PC-based systems.
GE Information Services	Has been developed primarily for the banking market.
Infinity	Some of the packages only run on Unix or Windows NT, not both.
Inssinc	License fee is high for small treasury departments.
IQ Financial Systems	Limited to a specific area of derivatives management in the treasury department.
KPMG Information Solutions	Might overwhelm small treasury teams that need little more than a spreadsheet.
Monis Software	Not a complete risk-management system. Doesn't handle trade capture.
SAP America	Implementation often demands a lot of time and support from across the company.
--	Unsuitable for companies that do not already run an SAP system.
Savid International	Runs on a limited range of computer operating systems.
Selkirk Financial Technologies	Too much functionality for the needs of some treasury departments.
Summit Systems	Too much functionality for the needs of some treasury departments.
Theoretics	Limitations in pricing derivatives.

Company	Operating Systems
Algorithmics	Unix, Windows NT
Derivatives Consulting	Windows 3.x, 95

FinancialCAD	Windows 95, NT, Unix
Financial Software Systems	Windows 95, NT, Unix
FXpress	Windows 3.x, 95, NT
GE Information Services	Windows NT, Unix
Infinity	Windows NT, Unix
Inssinc	Windows NT 4.0 or higher, WAN, intranet
IQ Financial Systems	Sun Solaris, Unix (Windows NT available soon)
KPMG Information Solutions	Windows NT, Unix, Netware
Monis Software	Windows NT, 95, Solaris
SAP America	Unix, Compaq, Digital, Unix HP, UX IBM, AIX Linux(***), Siemens, Reliant, Unix SUN, Solaris, Windows NT, IBM OS/400, IBM OS/390
--	Unix, Compaq, Digital, Unix HP, UX IBM, AIX Linux(***); Siemens, Reliant, Unix SUN, Solaris, Windows NT, IBM OS/400, IBM OS/390
Savid International	DOS, Windows 95, NT
Selkirk Financial Technologies	Windows NT, NetWare, Unix
Summit Systems	Windows NT, Unix
Theoretics	Sybase, Oracle, SQL Server, Access

Cited References:

Special Features: Table
Company Department Name: Accounting & Finance; Information Technology
Industry Names: Applications software; Software
Product Names: Business software packages NEC (737275)
Concept Terms: Technology evaluation

1230122/9 Links
Dissertation Abs Online

01230122 ORDER NO: NOT AVAILABLE FROM UNIVERSITY MICROFILMS INT'L.
OPTION PRICING MODELS--VALUATION PROBLEMS OF EXCHANGE TRADED OPTIONS
Original Title: OPTIONSMARTK-ANSATZE--ZU BEWERTUNGSPROBLEMEN BORSENNOTIERTER OPTIONEN

Author: PLOETZ, GEORG
Degree: DR.SOC.OEC
Year: 1990
Corporate Source/Institution: JOHANNES KEPLER UNIVERSITAET LINZ (AUSTRIA) (0586)
Source: Volume 5303C of Dissertations Abstracts International.
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Chapter I gives a basic introduction to put and call contracts. Options are characterized, the chances and risks inherent options are discussed. This chapter also shows the profit-and loss consequences of some elementary option trading strategies. Chapter II begins with the valuation of options. Determinants of option value are separated and their influence on option value is shown. Arbitrage restrictions on the value of a call and a put as a function of the current stock price, the exercise price and time to expiration are demonstrated. The Put-Call-Parity theorem for European and American Options is also developed. The purpose of chapter III is to derive and analyse an exact option pricing formula. The binomial option pricing formula and the Black/Scholes formula are developed and discussed. The basic idea is that an appropriately levered position in stock will replicate the future returns of a call (pricing by duplication). Dividends, different interest rates, the possibility of early exercise, taxes, margins and transaction costs are considered and alternative stock price movements are discussed. The sensitivity of call and put values to small changes in each of the fundamental variables is demonstrated. Chapter IV compares option-contracts with futures-contracts and shows how the valuation model for stock options can be modified to value options on Financial Futures (options on actuals and options on futures). Chapter V summarizes the preceding four chapters.

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ESSAYS ON VOLATILITIES IMPLIED BY OPTION PRICES

Author: SHEIKH, AAMIR MOHAMMAD
Degree: PH.D
Year: 1987
Corporate Source/Institution: UNIVERSITY OF CALIFORNIA, BERKELEY (0028)
CHAIRMAN: MARK RUBINSTEIN
Source: Volume 4905A of Dissertations Abstracts International.
PAGE 1230 . 145 PAGES
Descriptors: ECONOMICS, FINANCE
Descriptor Codes: 0508

This dissertation consists of three essays on return volatilities implied by option prices. The first essay contains a test of the efficiency of the Chicago Board Options Exchange relative to post-split increases in the volatility of common stocks. The Black-Scholes and Roll option pricing formulae are used to examine the behaviour of implied standard deviations (ISD's) around split announcement and ex-dates. Comparisons with a control group of stocks find no relative increase in ISD's of stocks announcing splits. A relative increase is, however, detected at the ex-date. Therefore, the joint hypothesis that (1) the Black-Scholes and Roll formulae are true and (2) the CBOE is efficient, can be rejected.

The more general behaviour and determinants of implied volatilities are examined in the second paper. The study covers three years, has a sample of thirty stocks and the S & P 100 and uses transactions data. Implied stock return volatilities are found to be significantly negatively related to stock prices and significantly positively related to forecasts of market return volatility. Moreover, ISD's continue to be serially and cross-sectionally correlated despite controlling for the effects of market variables.

The third paper studies the empirical pricing of S & P 100 calls with fourteen months of transactions data. By examining the pattern in implied volatilities, the methodology does not require an estimate of the index's return volatility and, moreover, simultaneously tests several alternative call pricing models. The findings indicate that the relative market prices of deep in-the-money calls are significantly greater than their Black-Scholes values. Moreover, for calls with the same exercise price, the shorter the time to maturity of a call, the higher its implied volatility. The ISD's of middle gamma calls tend to be higher than those of calls with extreme gammas. Also, implied volatilities from very high elasticity calls exceed those from other calls for part of the period examined. Nevertheless, none of the alternative call pricing models captures the pattern in implied volatilities.

01365938/9 **Links**
Fulltext available through: custom link . USPTO Full Text Retrieval Options

01365938 00-16925
Options and volatility

Abken, Peter A; Nandi, Saikat
Economic Review (Federal Reserve Bank of Atlanta) v81n3-6 pp: 21-35
Dec 1996
CODEN: ECRWDA
ISSN: 0732-1813 **Journal Code:** ECR
Document Type: Journal article **Language:** English **Length:** 15 Pages
Special Feature: Diagrams Equations References
Word Count: 7063

Abstract:

Since volatility of the underlying asset price is a critical factor affecting option prices, the modeling of volatility and its dynamics is of vital interest to traders, investors and risk managers. This modeling is a difficult task because the path of volatility during the life of an option is highly unpredictable. Clearly, the Black-Scholes assumption of constant volatility can be improved upon by incorporating time variations in volatility. While deterministic-volatility models can capture the dynamics of the volatility reasonably well, many of these option pricing models, such as ARCH models, are computationally expensive, especially for US options. The development of tractable stochastic-volatility models as well as more efficient methods of model parameter estimation are currently an area of intensive research. For both academic researchers and market practitioners, no consensus exists regarding the best specification of volatility for option pricing. Although a number of alternative approaches can account, at least partially, for the pricing deficiencies of the Black-Scholes model, none dominates as a clearly superior approach for pricing options.

Text:

Volatility is a measure of the dispersion of an asset price about its mean level over a fixed time interval. Careful modeling of an asset's volatility is crucial for the valuation of options and of portfolios containing options or securities with implicit options (for example, callable Treasury bonds) as well as for the success of many trading strategies involving options. The problem of pricing options is one confronting not only option traders but also, increasingly, a broad spectrum of investors. In particular, institutional investors' portfolios frequently contain options or securities with embedded options. More and more, riskmanagement

practices of financial institutions as well as of other corporate users of derivatives require frequent valuation of securities portfolios to determine current value and to gauge portfolios' sensitivities to market risk factors, including changes in volatility (see Peter A. Abken 1994). A model of volatility is needed for managing portfolios containing options (including derivatives and other securities containing options) for which market quotes are not readily available and that consequently must be marked to model (that is, valued by model) rather than marked to market. Accurate assessments of volatility are also key inputs into the construction of hedges, which limit risk exposures, for such portfolios.

Because of the central role that volatility plays in derivative valuation and hedging, a substantial literature is devoted to the specification of volatility and its measurement. Modeling volatility is challenging because volatility in financial and commodity markets appears to be highly unpredictable. There has been a proliferation of volatility specifications since the original, simple constant-volatility assumption of the famous option pricing model developed by Fischer Black and Myron S. Scholes (1973). This article gives an overview of different specifications of asset price volatility that are widely used in option pricing models.

The Effect of Volatility

A simple example will illustrate the importance of volatility for options. Consider a call option that gives the holder of the option the right to buy one unit of a stock at a future date T at a particular price (also called the strike or the exercise price of the option). Let the strike price of the option, denoted by K, be equal to $50. Note that the value of a call option at maturity is given by max(S sup I - K, 0), where S sup I denotes the stock price at the maturity of the option. Thus, the call option at its maturity has a value equal to the difference between the stock price at maturity and the strike price if S sup I > K and zero otherwise. If the stock price at maturity of the option is less than the strike price, the optionholder would rather buy the stock from the market than exercise the option and pay the higher strike price K for the stock. Now consider the following two stock price scenarios in which an option exists that has a strike price of $50: The average stock price (across the five states of the world) is $50 in both scenarios, but volatility is higher in the first scenario because of the wider dispersion of possible stock prices. In contrast to the constant average stock price in each scenario, the average option payoff is $7.50 in the low-volatility scenario and $15.00 in the high-volatility scenario. The reason is that the downside of the payoff to the optionholder is limited to zero because the option does not have to be exercised if the stock price at maturity is less than the strike price. The optionholder merely loses the price paid to the option writer (or seller) for the purchase of the option. However, the optionholder gains if the stock price at maturity is greater than the strike price. The higher the volatility, the higher is the probability that the option payoff at maturity will be greater than the strike price and consequently will be of value to the optionholder. Very high stock prices can increase the value of the call option at maturity without limit. However, very low stock prices cannot make the value of the option payoff at maturity less than zero. Thus the asymmetry of the payoffs due to the nature of the contract implies that volatility is of value to the optionholder at the maturity of the option.

In general, since the price of the option prior to its maturity is the expectation of the option payoff at maturity (discounted at an appropriate rate), an increase in the volatility of the underlying asset increases the expectation-and consequently the price of the option today.

In general, future volatility is difficult to estimate. While the historical volatility of an asset return is readily computed from observed asset returns (see Box 1), this measure may be an inaccurate estimate of the future volatility expected to prevail over the life of an option. The future volatility is unobservable and may differ from the historical volatility. Hence, unlike the other parameters that are important for pricing options (namely, the current asset price, the strike price, the interest rate, and time to maturity), the volatility input has to be modeled. For example, the BlackScholes option pricing model is a simple formula involving these five variables that prices European options. (Such options can be exercised only upon maturity. See John C. Cox and Mark Rubinstein 1985 for an exposition of the Black-Scholes formula.) The Black-Scholes model assumes that volatility is constant, the simplest possible approach. However, a preponderance of evidence (see Tim Bollerslev, Ray Y. Chou, and Kenneth E Kroner 1992) points to volatility being time-varying. In addition, that variation may be random or, equivalently, "stochastic." Randomness means that future volatility cannot be readily predicted using current and past information.
Before proceeding with an overview of the various approaches for treating time-varying volatility, the discussion examines a frequently documented phenomenon known as the volatility smile to motivate the consideration of different volatility specifications. The existence of the smile is an indication of the inadequacy of the constant-volatility Black-Scholes model. A common feature of all time-varying volatility models reviewed below is that they have the potential to give prices that are free of the Black-Scholes biases, such as the smile.

For the Black-Scholes model, the only input that is unobservable is the future volatility of the underlying asset. One way to determine this volatility is to select a value that equates the theoretical Black-Scholes price of the option to the observed market price. This value is often referred to as the implied (or implicit) volatility of the option. Under the Black-Scholes model, implied volatilities from options should be the same regardless of which option is used to compute the volatility. However, in practice, this is usually not the case. Different options (in terms of strike prices and maturities) on the same asset yield different implied volatilities, outcomes that are inconsistent with the Black-Scholes model. The pattern of the Black-Scholes implied volatilities with respect to strike prices has become known as the volatility smile. The existence of a smile also means that if only one volatility is used to price options with different strikes, pricing errors will be systematically related to strikes. The smile has also been shown to depend on options' maturities. The existence of pricing biases for the Black-Scholes model has been well documented. These biases have varied through time. For example, Rubinstein (1985) reports that short-maturity out-of-the-money calls on equities have market prices that are much higher than the Black-Scholes model would predict. On the other hand, since the stock market crash of 1987, the volatility smile has had a persistent shape, especially when derived from equity-index option prices-as the strike price of index-equity options

increases, their implied volatilities decrease. Thus, an out-of-the-money put (or in-the-money call) option has a greater implied volatility than an in-the-money put (or out-of-the-money call) of equivalent maturity.

Buying an out-of-the-money put can serve as insurance against market declines. The surprising severity of the market crash of 1987 increased the cost of crash protection, as manifested by a relatively high cost for out-of-the-money put options. Because the option price, for calls or puts, increases as volatility rises, higher option prices are associated with higher implied volatilities. Thus, relatively high out-of-the-money put prices are mirrored in high implied volatilities for those options.

The smile in equity index options is often referred to as a skew because the high implied volatilities for out-of-the-money puts (or, equivalently, for in-themoney calls) progressively decline as puts become further in-the-money (or as calls become further outof-the-money). Box 2 gives more detail about the volatility skew in the S&P 500 index-equity options. This article reviews two overarching approaches to generalizing the constant-volatility assumption of the Black-Scholes model that have appeared in the option pricing literature. Both lines of research have developed concurrently. The first approach assumes that variations in volatility are determined by variables known to market participants, such as the level of the asset price. Models of this type are referred to as deterministic-volatility models. This approach contrasts with the second, more demanding one, commonly called stochastic volatility, in which the source of uncertainty that generates volatility is different from, although possibly correlated with, the one that drives asset prices. Therefore, knowledge of past asset prices is not sufficient to determine volatility (using discretely observed prices). For reasons that will be explained more fully below, the first approach has been the most popular as a modeling strategy because of its relative simplicity.

(Table Omitted)

Captioned as: Box 1

The models under consideration in this article have been developed for equity, currency, and commodity options. Practitioners have also used the Black-Scholes model to price and hedge such options. Stochastic volatility is even more challenging to incorporate into models of fixed-income securities because of the complexities of modeling the term structure of interest rates. The Black-Scholes model has not been the benchmark model for pricing options in fixed-income markets, and less work has been done on stochasticvolatility bond pricing models. Thus, this topic is beyond the scope of this article.

Within the first approach, three types of models have been proposed. These are (1) implied binomial tree models, (2) general autoregressive conditional heteroscedasticity (GARCH) models, and (3) exponentially weighted moments models. Although somewhat arcane sounding on first reading, each will prove to have its own intuitive appeal. Each type of model also has the potential to closely or exactly match model option prices with actual market option prices. For the second approach involving stochastic volatility, models may be divided into those that have

closedform solutions for option prices and those that do not. Closed-form solutions refer to pricing formulas that are readily computed, given current computer technology. The distinction is a matter of practicality because the time it takes to compute prices is relevant to practitioners who trade options or hedge positions using options. Advances in computer technology will gradually blur the distinction among current stochastic-volatility models as time-consuming computations become less so in the future.

Deterministic Volatility
The future volatility depends on a constant and a constant proportion of the last period's volatility. In this case, the constant variance of the asset returns in the Black-Scholes formula can be replaced by the average variance that is expected to prevail from time t until time T (the expiration time), which is approximately given by and the Black-Scholes formula can continue to be used.

A more general case specifies volatility as a function of other information known to market participants. One alternative of this kind posits volatility as a function of the level of the asset price: C(S). One particular model of this type, known as the constant elasticity of variance (CEV) model, in which volatility is proportional to the level of the stock price raised to a power, appeared early in the option pricing literature (Cox and Steve Ross 1976). However, the CEV model proved not to be free of pricing biases (David Bates 1994). A more recent variation on this volatility specification was developed by Rubinstein (1994). Instead of assuming a particular form of the volatility function, Rubinstein's method effectively infers the dependence of volatility on the level of the asset price from traded options at all available strike prices. He calls the model "implied binomial trees" because the implied risk-neutral distribution (which depends on the volatility) of the asset price at maturity is inferred from option prices by constructing a so-called

binomial tree for movements of the asset price.' (See Box 3 for a discussion of risk-neutral valuation.) Related models have been proposed by Emanuel Derman and Iraz Kani (1994), Bruno Dupire (1994), and David Shimko (1993).

(Table Omitted)

Captioned as: Box 2

(Graph Omitted)

Captioned as: Volatility Smiles

In a recent empirical test of deterministic-volatility models, including binomial tree approaches, Bernard Dumas, Jeffrey Fleming, and Robert Whaley (1996) show that the Black-Scholes model does a better job of predicting future option prices. The option delta, which is derived from an option pricing model and measures the sensitivity of the option price to changes in the underlying asset price, can be used to specify positions in options that offset underlying asset price movements in a portfolio. The authors demonstrate that the Black-Scholes model resulted in better hedges than

those from models based on deterministic-volatility functions.

For their tests based on using S&P 500 index options prices, they conclude that "simpler is better" (20). The authors note that one reason for the better performance of the Black-Scholes model is that errors, from various sources, in quoted option prices distort parameter estimates for deterministic-volatility models and consequently degrade these models' predictions. However, hedging performance, which is a key consideration for risk managers and traders alike, has not been systematically tested across all option pricing models. As noted below, other research indicates that some versions of stochastic-volatility models may outperform the simple Black-Scholes model in terms of hedging.

ARCH Models. Autoregressive conditional heteroscedasticity (ARCH) models for volatility are a type of deterministic-volatility specification that makes use of information on past prices to update the current asset volatility and have the potential to improve on the Black-Scholes pricing biases. The term autoregressive in ARCH refers to the element of persistence in the modeled volatility, and the term conditional heteroscedasticity describes the presumed dependence of current volatility on the level of volatility realized in the past. ARCH models provide a wellestablished quantitative method for estimating and updating volatility.

ARCH models were introduced by Robert F. Engle (1982) for general statistical time-series modeling. An ARCH model makes the variance that will prevail one step ahead of the current time a weighted average of past squared asset returns, instead of equally weighted squared returns, as is done typically to compute variance (see Box 1). ARCH places greater weight on more recent squared returns than on more distant squared returns; consequently, ARCH models are able to capture volatility clustering, which refers to the observed tendency of high-volatility or low-volatility periods to group together. For example, several consecutive abnormally large return shocks in the current period will immediately raise volatility and keep it elevated in succeeding periods, depending on how persistent the shocks are estimated to be. Assuming no further large shocks, the cluster of shocks will have a diminishing impact as time progresses because more distant past shocks get less weight in the determination of current volatility.

Some technical features of ARCH models also make them attractive compared with many other types of option pricing models that allow for time-varying volatility. In an ARCH model, the variance is driven by a function of the same random variable that determines the evolution of the returns.2 In other words, the random source that affects the statistical behavior of returns and volatility through time is the same. As a result, volatility can be estimated directly from the time series of observed returns on an asset. In contrast, the direct estimation of volatility from the returns process is very difficult using stochastic-volatility models.

(Table Omitted)

Captioned as: Box 3
There are many different types of ARCH models that have a wide variety of applications in macroeconomics and finance. In finance, the two most

popular ARCH processes are generalized ARCH (GARCH) (Bollerslev 1986) and exponential GARCH (EGARCH) (Daniel B. Nelson 1991). The technical distinctions are beyond the scope of this article; however, researchers have tended mostly to use the GARCH process and its variations for option pricing.' Although GARCH captures the evolution of the variance process of asset returns quite well, it turns out that there is no easily computable formula, like the Black-Scholes formula, for European option pricing under a GARCH volatility process. Instead, computer-intensive methods are used to simulate the returns and the volatility under the risk-neutral distribution in order to compute European option prices and hedge ratios. (Recent examples include Kaushik Amin and Victor Ng 1993 and Jin C. Duan 1995.)

Owing to the lack of efficient pricing and hedging formulas for GARCH models, practitioners-and some researchers-often substitute the expected average variance from a GARCH model for the variance input in the Black-Scholes formula (see Engle, Alex Kane, and Jaesun Noh 1994). However, the BlackScholes formula does not hold if the variance of asset returns follows a GARCH process; such a substitution is theoretically inconsistent but may work in practice. Another problem with using the extant GARCH option pricing models is that they do not value American options, which account for most of all traded options. American options can be exercised at any time before maturity, and consequently their prices equal or exceed the prices of comparable European options by the value of this extra flexibility, termed the early-exercise premium. A simple approximation is achieved by adding an estimate of the early-exercise premium to the European price derived from a GARCH model. (There are numerical methods, such as Monte-Carlo simulations, that can value American options, but these methods are currently impractical because of the enormous number of computations required.) The value of the early-exercise premium is often evaluated using the Barone-Adesi-Whaley (1987) formula for the Black-Scholes model.

An early test of a GARCH option pricing model is Engle and Chowdhury Mustafa (1992), who examined S&P 500 index options. Their results show that the GARCH pricing model cannot account for all of the pricing biases observed in the option market. Engle, Kane, and Noh (1994) compared the trading profits resulting from a particular trading rule by using two alternatives for the variance forecasts needed for Black-Scholes: the variance forec

ast from a GARCH model and the variance forecast in the form of the Black-Scholes implied volatility from a previous period. As noted above, plugging a GARCH forecast into the Black-Scholes formula is ad hoc; however, in an experiment using S&P 500 index options, Engle, Kane, and Noh produced greater hypothetical trading profits using the GARCH volatility forecast than they did using the Black-Scholes implied volatility.

To summarize, although GARCH is a good description of the evolution of the variance process of the asset returns, option pricing models based on GARCH are computationally demanding and may not be very useful for many practitioners given current computing technology. In addition, only a limited number of empirical tests have been done to date on GARCH option pricing models; as a consequence, it is hard to say how well the model does in pricing options and evaluating hedge ratios.4

Exponentially Weighted Moments Models. David G. Hobson and L.C.G. Rogers (1996) propose a new type of option pricing model for time-varying volatility that also has the potential to match the observed volatility smile. Their mathematical specification allows past asset-price movements to feed back into current volatility. This characteristic has some of the flavor of a GARCH model in terms of a similar feedback effect; however, the type of feedback can be much more general than encountered in standard GARCH models. Also like GARCH, but unlike standard stochastic-volatility models, there is only one source of uncertainty that drives both the asset price and its volatility.5

The Hobson-Rogers model captures past asset price volatility through a so-called offset function. The feedback relationship is primarily embodied in the functional dependence of the volatility on the offset function. The intuition behind the offset function is apparent from its form:
Stochastic Volatility

Stochastic volatility implies that the future level of the volatility cannot be perfectly predicted using information available today. The popularity of stochastic volatility in option pricing grew out of the fact that distributions of the asset returns exhibit fatter tails than those of the normal distribution (Benoit Mandelbrot 1963 and Eugene F. Fama 1965). In other words, the observed frequency of extreme asset returns is much higher than would occur if returns were described by a normal distribution. Stochastic-volatility models can be consistent with fat tails of the return distribution. The occurrence of fat tails would imply, for example, that out-of-the-money options would be underpriced by the Black-Scholes model, which assumes that returns are normally distributed. However, the fat-tailed asset return distributions can also come from ARCHtype volatility as well as from jumps in the asset returns (Robert C. Merton 1976). Stochastic-volatility models could also be an alternative explanation for skewness of the return distribution. Despite the relative complexity of stochastic-volatility models, they have been popular with researchers, and additional justification for these models has recently come to light in the literature on asymmetric information about the future asset price and its impact on traded options.7

In a stochastic-volatility model, volatility is driven by a random source that is different from the random source driving the asset returns process, although the two random sources may be correlated with each other. In contrast to a deterministic-volatility model in which the investor incurs only the risk from a randomly evolving asset price, in a stochastic-volatility environment, an investor in the options market bears the additional risk of a randomly evolving volatility. In a deterministicvolatility model, an investor can hedge the risk from the asset price by trading an option and a risk-free asset based on a risk exposure computed using an option pricing formula (see Cox and Rubinstein 1985). (Equivalently, the option's payoff can be replicated by trading the underlying asset and a risk-free asset.) However, with a random-volatility process, there are two sources of risk (the risk from the asset price and the volatility risk); a risk-free portfolio cannot be created as in the Black-Scholes model. After hedging, there is a residual risk that stems from the random nature of the volatility process. Since there is no traded

asset whose payoff is a known function of the volatility, volatility risk cannot be perfectly hedged. In order to bear this volatility risk, rational investors would demand a "volatility risk" premium, which has to be factored into option prices and hedge ratios.8

A feature of stochastic-volatility models that is not shared by deterministic-volatility models is that the price of an option can change without any change in the level of the asset price. The reason is that the option price is driven by two random variables: the asset price and its volatility. In stochastic-volatility models, these two variables may not be perfectly correlated, implying that the expected volatility over the life of the option may change without any change in the asset price. The change in volatility alone can cause the option price to change.

Most stochastic-volatility models assume that volatility is mean reverting. That is, although volatility varies from day to day, there is a presumed long-run level toward which volatility settles in the absence of additional shocks. Market participants refer to this feature as "regressing to the mean" of the volatility. (The evidence for this phenomenon is especially strong in markets for interest rate derivatives. See, for example, Robert Litterman, Jose Scheinkman, and Laurence Weiss 1991 and Amin and Andrew Morton 1994.)

Stochastic-volatility models can be classified into two broad categories: those that lack closed-form solutions for European options and those that have closedform solutions.9 Even if a model's parameters are known, most stochastic-volatility option pricing models are computationally demanding for pricing European options and especially so for pricing American options. A notable exception is the model of Steven Heston (1993) that gives closed-form solutions for prices and hedge ratios of European options. All other models compute option prices either by numerically solving a complicated partial differential equation or by Monte Carlo simulation. However, many key parameters are not readily estimated from data, particularly those of the volatility process, because, unlike the returns process of the underlying asset, the volatility process is not directly observable. Since parameter estimation is often time-consuming, the lack of readily computed solutions for option prices in many stochasticvolatility models can compound the difficulties of estimation.

Although stochastic-volatility pricing models give only closed-form solutions for European options, a good approximation for the price of an American option can be obtained by adding an early exercise premium using the Barone-Adesi-Whaley approximation in the same way as for ARCH models. Examples of this practice are in Hans J. Knoch (1992) and Bates (1995). At present, the only other way to price American options under stochastic volatility is by solving a second-order partial differential equation (Angelo Melino and Stuart Turnbull 1992), which is extremely computationally burdensome.

Stochastic-Volatility Option Models without Closed-Form Solution. John C. Hull and Alan White (1987), Louis O. Scott (1987), and James B. Wiggins (1987) were among the first to develop option pricing models based on stochastic volatility. Hull and White as well as Scott made the questionable assumption that the risk premium of volatility is zero-that

is, the volatility risk is not priced in the options market-and that volatility is uncorrelated with the returns of the underlying asset. Wiggins, who also assumed a zero-volatility risk premium, found that the estimated option values under stochastic volatility were not significantly different from Black-Scholes values, except for long maturity options. For equity options, Christopher Lamoureux and William Lastarapes (1993) offer evidence against the assumption of a zero-volatility risk premium. For currency options, Melino and Turnbull (1992) found that a random-volatility

model yields option prices that are in closer agreement with the observed option prices than those of the Black-Scholes model. While the numerical methods and computers currently available allow computation of these stochasticvolatility option prices, they are still largely impractical for determining hedge ratios, which are vital to marketmakers, dealers, and others. As a result, these stochastic-volatility models may not currently be useful for practitioners. Nevertheless, development of stochasticvolatility models continues as researchers attempt to find more tractable models.

Stochastic-Volatility Models with Closed-Form Solutions. Elias M. Stein and Jeremy C. Stein (1991) develop a European option pricing model under stochastic volatility that is somewhat easier to evaluate than the models described above." Although less computationally expensive than the other models, the authors make the unrealistic assumption of zero correlation between the volatility process and the returns of the underlying asset.

Heston (1993) was the first to develop a stochasticvolatility option pricing model for European equity and currency options that can be easily implemented, is computationally inexpensive, and allows for any arbitrary correlation between asset returns and volatility." The model gives closed-form solutions not only for option prices but also for the hedge ratios like the deltas and the vegas of options. (Delta and vega measure the sensitivity of the option price to changes in the asset price and to changes in the volatility, respectively. Knowledge of these measures enables the construction of hedges for options or for portfolios containing embedded options.)

The empirical work done on Heston's model includes that by Knoch (1992), Saikat Nandi (1996), and Bates (1995). In order to take into account the possibility of sudden large price movements, such as the crash of 1987, Bates generalizes Heston's model by allowing for jumps in asset prices. While Knoch and Bates study the pricing issues of this model for options on foreign currencies, Nandi examines both pricing and hedging issues using the S&P 500 index options. All of these studies find that Heston's model is able to generate prices that are in closer agreement with market option prices than those of the Black-Scholes model. However, it is not the case that this model is able to explain all biases of the Black-Scholes model. While it is true that the remaining pricing biases are of smaller magnitude than those of the Black-Scholes model, Nandi finds that there are still substantial biases for out-of-the-money puts and calls in the S&P 500 index options market. In particular, the model underprices out-of-the-money puts and overprices out-of-the-money calls. It is possible that the square-root volatility process and therefore the model itself are misspecified. This misspecification would be unfortunate because the

particular form of the volatility process is what makes this stochastic-volatility model tractable.

If the Black-Scholes assumption of constant volatility were true, a hedge portfolio (hedged against the risk from the asset price) would simply earn the riskfree rate of return. Such a portfolio would typically consist of a position in the underlying asset and an option. The position would be altered through time by trading, based on the formulas for hedge ratios determined by the Black-Scholes model (see Cox and Rubinstein 1985) or other option pricing models. When volatility is stochastic, as it probably is in the real world, hedging using the Black-Scholes model does not result in risk-free positions. A stochastic-volatility model may do a better job of hedging against price and volatility risks. Nandi (1996) finds that for S&P 500 index options the returns of a hedge portfolio constructed using Heston's stochastic-volatility model come closer to matching a risk-free return through time better than hedge portfolio returns obtained using the Black-Scholes model.

Volatility Jumps. All the time-varying volatility models that have been discussed so far assume that the volatility of the underlying asset as well as its price evolves "smoothly," though randomly, through time: there are no jumps in the volatility process. However, a likely cause of financial market volatility is the arrival of information and its subsequent incorporation into asset prices through trading. To the extent that information-"news"-arrives in discrete lumps, it is possible that volatility shifts between episodes of low and high volatility. For example, uncertainty about an impending news release (concerning some macroeconomic variable, like an anticipated change in the fed funds rate by the Federal Open Market Committee) may cause the volatility of an asset price to rise. However, after a few rounds of trading, with the information having been incorporated into asset prices, volatility may revert back to its previous level.

To account for jumps like those in the example, Vasantlilak Naik (1993) develops a pricing model for European options in which volatility switches between low and high levels. Each level or "regime" is expected to last for a certain period of time that is not known a priori. One tractable version of his model assumes that the risk from the volatility jumps is not priced by market participants. The model takes the same parameters that enter the Black-Scholes formula as well as additional parameters such as the probabilities of jumps from one regime to another regime, given that volatility is currently in a particular regime. Naik finds that short-maturity options are much more sensitive to volatility shifts than long-maturity options. The reason is that, over a long period of time, expected upward and downward jumps in volatility are canceled by each other, resulting in a volatility that is close to the normal level. This model has not been empirically tested and therefore cannot yet be evaluated against other stochasticvolatility models. In general, jump models can be difficult to verify empirically because jumps occur infrequently. The parameters of such models may be imprecisely estimated using relatively small historical data series on option prices or underlying asset prices.

Conclusion

Since volatility of the underlying asset price is a critical factor affecting option prices, the modeling of volatility and its dynamics is of vital interest to traders, investors, and risk managers. This modeling is a difficult task because the path of volatility during the life of an option is highly unpredictable. Clearly, the BlackScholes assumption of constant volatility can be improved upon by incorporating time variation in volatility. While deterministic-volatility models can capture the dynamics of the volatility reasonably well, many of these option pricing models, such as ARCH models, are computationally expensive, especially for American options. Deterministic-volatility option pricing models have the advantage that most parameters can be estimated directly from the observable time series of returns data. However, superior hedging performance of such models relative to that of the Black-Scholes model has not been demonstrated. On the other hand, there is evidence that some stochastic-volatility option pricing models provide better hedges than BlackScholes, although for stochastic-volatility option pricing models and volatility-jump models, parameter estimation is typically demanding and problematic.

The development of tractable stochastic-volatility models as well as more efficient methods of model parameter estimation are currently an area of intensive research. For both academic researchers and market practitioners, no consensus exists regarding the best specification of volatility for option pricing. Although a number of alternative approaches can account, at least partially, for the pricing deficiencies of the Black-Scholes model, none dominates as a clearly superior approach for pricing options.

Footnote:

Notes

Footnote:

1. Instead of taking a wide range of values as in the real world, a binomial tree restricts stock price movements at any moment in time to be either up with one probability or down with another (see Cox and Rubinstein 1985).

2. Although there is one source of uncertainty that drives both the asset returns and the volatility in a GARCH model, which is a special case of ARCH, the asset returns are distributed continuously-that is, one out of an infinite number of possible uncertain returns will be realized over the next period. Therefore, with discrete trading (as in a GARCH model), it is not possible to replicate all possible uncertain returns outcomes (see Duffie and Huang 1985) by trading in the option and a risk-free asset (or, equivalently, a unique risk-free portfolio cannot be created by trading in the underlying asset and an option). Hence, a risk premium associated with the returns of the underlying asset is required in a GARCH model.

3. The NGARCH of Engle and Ng (1993) is one such variation.

4. GARCH can capture the volatility smile. In a GARCH model, such as Duan's (1995), the price of an option, besides being a function of the variables

that appear in the

Footnote:

Black-Scholes formula, is also a function of variables that describe the time variation in volatility as well as a variable that accounts for the risk premium of the asset returns, that is, the excess return over a risk-free asset. Since the risk premium summarizes investor preferences, the GARCH option pricing model is not preference-free-a key attribute of the Black-Scholes model. Duan shows that under the riskneutral distribution, the value of the GARCH variance at a point in time is negatively correlated with past asset returns if the risk premium of the asset is greater than zero. Such a negative correlation can give rise to negative skewness in the risk-neutral distribution, which seems to be a feature of the empirical data, as discussed in Bates (1995). GARCH models can therefore potentially generate option prices that are consistent with the observed volatility skew.

5. The Hobson-Rogers model is also preference-free. This model, unlike GARCH, is set in continuous time. There being a single source of uncertainty and continuous trading, all possible uncertain returns outcomes of the underlying risky asset over the next period can be replicated by trading in an option and a risk-free asset (Duffie and Huang 1985), and there is no need for any risk premium of returns.

Footnote:

6. The Hobson-Rogers equation actually is written with an integral rather than a summation.

7. Back (1993) shows how stochastic volatility might be introduced endogenously in asset markets due to asymmetric information about the future price of an underlying asset on which an option is traded.
8. In an ARCH option pricing model the risk premium that enters is the risk premium of asset returns and not the risk premium of volatility.

9. For American options, a closed-form solution in a stochasticvolatility model has not yet been derived.

10. Their model requires the numerical evaluation of a twodimensional integral (that is computationally easier) rather

Footnote:

than the solution of a second-order partial differential equation. However, the volatility process is allowed to become negative, an undesirable feature.

11. Heston's (1993) paper gives the closed-form solution for prices of call options. The price of a put option can be easily obtained using the put-call parity for European options.

12. A tail of a probability distribution is the area under the distribution

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at assigns probabilities to extreme outcomes. For example, in the typical bell-shaped normal distribution, there are two tails, the right tail and the left tail, that slowly taper off.
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THIS IS THE FULL-TEXT.

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